MALE-FEMALE PRODUCTIVITY DIFFERENTIALS: THE ROLE OF ABILITY AND INCENTIVES*

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Abstract

We consider the response to incentives as an explanation for productivity differences within a firm that paid its workers piece rates. We provide a framework within which observed productivity differences can be decomposed into two parts: one due to differences in ability and the other due to differences in the response to incentives. We apply this decomposition to male and female workers from a tree-planting firm in the province of British Columbia, Canada. We provide evidence that individuals do react differently to incentives. However, while the women in our sample reacted slightly more to incentives than did the men, the average difference is not statistically significant. The productivity differential that men enjoyed arose because of differences in ability, strength in our application.

Résumé

Dans cette étude, nous étudions la réaction aux incitations offertes aux travailleurs afin d'expliquer les différences de productivité de travailleurs observés dans une entreprise qui les a payés à la pièce. Nous développons un modèle pour lequel les différentiels de productivité peuvent être décomposés en deux parties : une partie liée aux différences d'habilité et une autre due aux différences de la réponse aux incitations. Nous appliquons cette décomposition aux travailleurs (hommes et femmes) en provenance d'une entreprise de plantation d'arbres située en Colombie Britannique. Nos résultats suggèrent que les individus sont hétérogènes quant à leur réponse aux incitations. Pourtant, bien que les femmes y réagissent sensiblement plus que les hommes, cette différence n'est pas statistiquement significative. Le différentiel de productivité appara^seulement dû des différences d'habilité, ce qui représente la force dans notre étude.

1. Introduction and Motivation

Economists have long been interested in measuring and explaining differences in labour-market performance between men and women. Traditionally, attention has focused on the earnings premium enjoyed by men and its relationship to productivity differences; see, for example, Gunderson (1989). Following Oaxaca (1973), the empirical implementation of human-capital models permits the decomposition of the premium in two parts: one explained by differences in economic characteristics and the other a residual. Empirical results typically suggest that a substantial proportion of the earnings premium is unexplained by differences in observed characteristics; see Blau, Ferber, and Winkler (1998). While these residuals are consistent with labour-market discrimination, they may also reflect behavioural differences between groups; see, for example, Bowles, Gintis, and Osborne (2001). Men and women may differ with respect to motivation and aggressiveness, attributes that may be reflected in labour-market outcomes. Hakim (2000) has also provided a general discussion of these issues from a sociological perspective, concentrating on differences in male and female attitudes towards work and careers. From an economic perspective, Becker (1985) has suggested that women have a comparative advantage in high-effort domestic tasks which may cause them to supply less effort in the labour market than men.

Decomposing earnings, statistically, is difficult in the presence of unobserved behavioural differences, such as effort. Counterfactual calculations based on regression analyses breakdown when individuals differ in unobserved characteristics that are correlated with covariates of interest; see, for example, Heckman (1997). In general, two empirical strategies have been pursued, both of which require special data. In one, researchers have supplemented broad-based earnings data with measures of personality traits thought to be correlated with behaviour. Early examples of this approach include Wise (1975) and Duncan (1976). Recently, Long (1995) found significant differences in the effect of motivational factors on income among men and women.

Similarly, Nyhus and Pons (2002) found that personality traits appear to affect male and female earnings differently, suggesting that the male-female earnings gap will be affected by controlling for behaviour. Duncan and Dunifon (1998) controlled for potential reverse causality (such as success in the labour market affecting personality) using personality measures recorded years before the data on earnings were gathered. They found that motivational traits (such as preferences for challenges and fear of failure) as well as behavioural measures (such as church attendance and participation in social clubs) significantly affected standard earnings functions.

A second, and perhaps more direct approach, is to test whether men and women react differently to the incentives inherent within various compensation systems observed in the labour market. Methodologically, this approach is closely related to that in research concerned with measuring the impact of compensation systems on worker productivity; see, for example, Bull, Schotter, and Weigelt (1987), Paarsch and Shearer (1999,2000), Lazear (2000), Haley (2003), and Shearer (forthcoming). Recent experimental evidence suggests that men and women react differently in competitive situations; see Gneezy, Neiderle, and Rustichini (forthcoming). This may explain partly the lower promotion rates experienced among female employees as well as the phenomenon often referred to as the *glass ceiling*.[1]

In this paper, we consider differences in the reactions of men and women to a real-world, labour-market incentive system as a possible explanation of productivity differences between the two sexes. We concentrate on piece-rate workers and compare the elasticity of worker effort with respect to changes in the piece rate. We exploit a unique data set created from the personnel records of a tree-planting firm operating in British Columbia. These data contain information on daily worker productivity under a variety of piece rates along with worker characteristics. Our data show that, on average, men planted more trees per day than women, on the order of eleven percent.

[1] In the *Harvard Business Review*, June 2003, it was reported that in 2003 women made up more than half the managerial and professional labour pool, but held only one percent of chief executive positions in Fortune 500 companies.

This is in contrast to the experiments of Gneezy *et al.* who found no difference in performance when subjects were paid piece rates. Since this difference is conditional on work conditions and piece rates, we ignore discrimination as a possible explanation, concentrating on inherent productivity differences between men and women.[2] In particular, we seek to measure how much of this difference is due to differences in worker reactions to the piece-rate incentive system.

Our approach is to use economic theory as an identifying assumption to interpret observed data. As such, we add to the recent literature on applying structural-econometric methods to data from firm records in order to investigate incentive issues; see, for example, Ferrall and Shearer (1999), Paarsch and Shearer (1999,2000), Haley (2003), and Shearer (forthcoming) as well as Copeland and Monet (2002). Estimating structural-econometric models that explain earnings differences was first proposed and implemented by Bowlus (1997) and later by Bowlus and Eckstein (2002). We model worker effort choices explicitly. Effort is a function of the incentives in place within the firm as well as unobserved worker characteristics. Deriving optimal decision rules on the part of the worker and incorporating these rules directly into the estimation procedure allows us to identify the determinants of worker effort and productivity.

Behaviouralists describe incentive-enhancing preferences as those that increase a worker's equilibrium effort level as a function of his reward; see Bowles, Gintis, and Osborne (2001). Here, we focus on differences in parameters that determine a worker's cost of effort. In our model, this can happen two ways, either from differences in a worker's ability or from differences in a worker's reaction to piece rates. Differences in ability affect the effort level, but not the percentage change in effort with respect to the piece rate, the elasticity. We show that differences in observed productivity, for a given piece rate, can be decomposed into differences in ability and differences in the reaction to incentives. We use our model to test whether women react to piece rates in an observably-different way from men.

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[2] Interviews with firm managers revealed that workers were randomly allocated to working conditions and piece rates.

Identifying parameters that affect effort requires modelling the way these parameters affect the distribution of observed productivity. Our model allows us to identify differences in reaction from difference in ability because these two factor affect the variance of productivity differently. Individuals who react a great deal to incentives take advantage of favourable economic conditions to increase productivity; ability affects average productivity while reaction affects average productivity as well as the variance of productivity. We show that our framework allows us to rank workers in terms of their response to incentives and to test whether this response is homogenous. In addition, we incorporate individual characteristics into the model to test whether women react differently from men.

Our results suggest that individuals do differ with respect to their reactions to incentives; effort elasticities are heterogeneous. However, while the women in our sample reacted more to incentives than did the men, this difference is not statistically significant. Observed productivity differences within our sample arose solely from differences in ability, strength in our application.

Our paper is organized as follows: In section 2, we provide some institutional details concerning the tree-planting industry in British Columbia, while in section 3 we present our data. In section 4, we develop a model of worker effort decisions and present our productivity decomposition. In section 5, we present our results, while in section 6 we summarize and conclude.

2. Institutional Details

British Columbia is one of the largest producers of timber in North America; some twenty-five percent of North American softwood lumber supply is produced in this province. While timber is a renewable resource, active reforestation can increase the speed at which forests regenerate and also allows one to control for species composition, something that is difficult to do in the case of natural regeneration. Reforestation is central to a steady supply of lumber to the North American market.

In British Columbia, extensive reforestation is undertaken by both the Ministry of Forests and the major timber-harvesting firms.[3]

The mechanics of this reforestation are straightforward. Prior to the harvest of any tract of coniferous timber, random samples of cones are taken from the trees on the tract, and seedlings are grown from the seeds contained in these cones. This ensures that the seedlings to be replanted are compatible with the local micro-climates and soil as well as representative of the historical species composition.

Tree planting is a simple, yet physically exhausting, task. It involves digging a hole with a special shovel, placing a seedling in this hole, and then covering its roots with soil, ensuring that the tree is upright and that the roots are fully covered. The effort required to perform the task depends on the terrain on which the planting is done. In general, the terrain can vary a great deal from site to site. In some cases, after a tract has been harvested, the land is prepared for planting by burning whatever slash timber remains and by *screefing* the forest floor. Screefing involves removing the natural build-up of organic matter on the forest floor so that the soil is exposed. Screefing makes planting easier because seedlings must be planted directly in the soil. Sites that are relatively flat or that have been prepared are much easier to plant than sites that are very steep or have not been prepared. The typical minimum density of seedlings is about 1,800 stems per hectare, or an inter-tree spacing of about 2.4 metres, although this can vary substantially.[4] An average planter can plant between 700 and 900 trees per day, about half an hectare, depending on conditions. An average

[3] In British Columbia, nearly 90 percent of all timber is on government-owned (Crown) land. Basically, the Crown, through the Minister of Forests, sells the right to harvest the timber on this land in two different ways. During our sample period, the most common way was charging administratively-set prices to a small number of firms who held Tree Farm Licenses or other similar agreements. The terms of these agreements were negotiated over the last three-quarter century, and require that the licensee adopt specific harvesting as well as reforestation plans. About ninety percent of all Crown timber is harvested by firms holding Tree Farm Licenses or similar agreements. The second, and less common way, to sell timber is at public auction through the Small Business Forest Enterprise Program. In this case, the Ministry of Forests assumes the responsibility of reforestation.

[4] One hectare is an area 100 metres square, or 10,000 square metres. Thus, one hectare is approximately 2.4711 acres.

harvested tract is around 250 hectares.

Typically, tree-planting firms are chosen to plant seedlings on harvested tracts through a process of competitive bidding. Depending on the land-tenure arrangement, either a timber-harvesting firm or the Ministry of Forests will call for sealed-bid tenders concerning the cost per tree planted, with the lowest bidder's being selected to perform the work. The price received by the firm per tree planted is called the *bid price*. Bidding on contracts takes place in the late autumn of the year preceding the planting season, which runs from early spring through to late summer. Before the bidding takes place, the principals of the tree-planting firms typically view the land to be planted and estimate the cost at which they can complete the contract. This estimated cost depends on the expected number of trees that a planter will be able to plant in a day which, in turn, depends on the general conditions of the area to be planted.

Planters are predominantly paid using piece-rate contracts, although fixed-wage contracts are sometimes used instead. Under piece-rate contracts, planters are paid in proportion to their output. Generally, no explicit base wage or production standard exists, although firms are governed by minimum-wage laws. Output is typically measured as the number of trees planted per day, although some area-based schemes are used as well. An area-based scheme is one under which planters are paid in proportion to the area of land they plant in a given day, assuming a particular stem density.

Our data were collected from a medium-sized, tree-planting firm that employed a total of 155 planters throughout the 1994 tree-planting season. This firm paid its planters piece rates exclusively; daily earnings for a planter were determined by the product of the piece rate and the number of trees the planter planted on that day. Sites to be planted were divided into plots. For each plot, the firm decided on a piece rate. This rate took into account the expected number of trees that a planter could plant in a day and the expected wage the firm wanted to pay. Thus, the piece rate should be negatively correlated with good planting conditions. All planters planting

Table 1
Summary Statistics

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Number of Trees	3960	786.48	307.39	120	2260
Piece Rate	3960	0.25	0.06	0.13	0.48

on the same plot received the same piece rate; no matching of planters to planting conditions occurred, so even though planters may be heterogeneous, the piece rate received was independent of planter type. Planters were assigned to plots as they disembarked from the ground transportation that took them to the planting site. Thus, to a first approximation, planters were randomly assigned to plots.

3. Data

Our data set contains information on the piece rate received by each planter as well as that planter's age, gender, and daily productivity. We considered only those observations for which the planter received the same piece rate for the entire day of planting. This eliminated the problem of aggregating trees planted under different piece rates. The summary statistics for the planting data, 3960 planting days concerning 89 workers, are presented in Table 1.[5]

The data are from a five-month period during the spring and summer of the 1994 planting season. On average, workers planted 786 trees per day at an average piece rate of 25 cents per tree. Our data set contains information on 31 different contracts, each defined by a different piece rate ranging from 13 cents per tree to 48 cents per tree.

Of the 89 workers in the sample, 66 (or 74 percent) were men. In Table 2, we summarize the productivity of male and female planters, separately. On average,

[5] We restricted the sample to planters whom we observed at least twenty planting days. We also purged outliers from the original data set by eliminating all observations for which earnings were less than the minimum wage; see Paarsch and Shearer (1999) for details.

Table 2
Summary Statistics: Men versus Women

	Observations	Trees		Earnings	
		Mean	Standard Deviation	Average	Standard Deviation
Male Planters	3080	802.70	314.22	189.25	58.50
Female Planters	880	729.73	274.94	164.13	48.43

women planted fewer trees than men, approximately ten percent.

Productivity is affected by effort as well as planting conditions. To compare productivity, holding planting conditions constant, we conditioned on the planting environment in which the employee worked. Since the firm determined the piece rate as a function of planting conditions, we take the piece rate as summarizing all relevant information regarding those conditions. Rather than specify a functional form to condition on the piece rate in a regression, we included dummy variables indicating each piece rate; *i.e.*, we considered the regression of daily productivity (in logarithmic form) on piece-rate (planting-condition) dummy variables (the DB_js) as well as a dummy variable indicating gender (DM_i which is one for men and zero for women)

$$\log Y_{ij} = \beta_0 + \beta_1 DM_i + \sum_{j=2}^{31} \beta_{2,j} DB_j + \beta_3 AGE_i + \beta_4 AGESQ_i + \epsilon_{ij}. \tag{3.1}$$

Here, AGE_i and $AGESQ_i$ denote the age and age squared of planter i. Estimated parameters, excluding those for the planting-condition dummy variables, are presented in Table 3.

The results from Table 3 suggest that men are approximately eleven percent more productive than women at planting trees when planting conditions (the piece rate) and age are held constant. In subsequent sections, we investigate the causes of this productivity difference, concentrating on two possible explanations. First, male planters may be more productive than female planters because of ability (strength in

Table 3
Productivity Regression Parameter Estimates
Sample Size = 3960

Parameter	Estimate	Std. Error	p-Value
β_0	6.954	0.033	0.000
β_1	0.113	0.013	0.000
β_3	0.017	0.002	0.000
β_4	$-1.7(-4)$	$3.5(-5)$	0.000

Note: $3.5(-5)$ denotes 3.5×10^{-5}.

the case of tree-planting); namely, their cost of effort may be lower. Second, male planters may be more sensitive to incentive pay than female planters; namely, the elasticity of effort with respect to the piece rate may be higher for men than for women.

The elasticity of effort with respect to the piece rate as well as the cost of effort are inherently unobservable parameters. Their identification requires knowledge of how they affect the distribution of observed productivity, which requires developing and estimating a structural model of worker reactions to incentives. In the next section, we develop a simple model that allows us to identify the relative importance of each of these factors in explaining the observed productivity gap between men and women.

4. Model

We model worker productivity decisions as a function of the piece rate and the cost of effort, extending the model of Paarsch and Shearer (1999) to admit heterogeneity in response to incentives. We assume that planters are risk neutral, so the pay-off function of worker i can be written as

$$U(W, E) = W - C_i(E)$$

where W denotes earnings and $C_i(E)$ represents the planter's cost of effort. Under piece rates, the earnings function is

$$W = rY$$

where Y denotes planter output and r denotes the piece rate. We assume the following cost-of-effort function:

$$C_i(E) = \frac{\kappa_i \gamma_i}{\gamma_i + 1} E^{\frac{\gamma_i}{(\gamma_i+1)}} \quad \gamma_i > 0,\ \kappa_i > 0.$$

Under this assumption, heterogeneity can take two forms. First, heterogeneity in κ_i captures differences in ability. A low κ_i increases output at all piece rates. Second, because γ_i measures the elasticity of worker effort with respect to the piece rate, heterogeneity in γ_i captures differences in reactions.

Daily output is assumed to follow

$$Y = ES$$

where S is a random productivity shock drawn from the distribution $F(s)$. The shock represents planting conditions which are beyond the planter's control, such as the slope of the terrain, hardness of the ground, and the amount of ground cover. The logarithm of the productivity shock is assumed to follow a normal distribution with mean μ and variance σ^2, so the probability density function of S takes the form

$$f(s) = \frac{1}{s\sigma}\phi\left(\frac{\log s - \mu}{\sigma}\right)$$

where $\phi(\cdot)$ represents the standard normal probability density function.

We assume that s, a realization of S, is observed by planters before they choose their effort levels, but after they accept a contract. Note that the firm does not observe s; it only observes the parameters of the distribution of S, μ and σ^2. Thus, while a planter can observe average planting conditions before he or she begins to plant, the exact nature of the terrain to be planted is only revealed once planting begins. The timing of events in our model is as follows:

1. for a particular contract to be planted, Nature chooses the pair (μ, σ^2), the parameters of the distribution of S;
2. the firm observes (μ, σ^2), and then chooses a piece rate r;
3. the planter observes (μ, σ^2, r), and accepts or rejects the contract;
4. if the planter accepts the contract, then he is randomly assigned to plant a particular plot of the contract;
5. for each plot, Nature chooses s, a particular value of S;
6. the planter observes s, and chooses an effort level e producing output y;
7. the firm observes y, and pays earnings ry.

To solve the model, we work backwards. First, we solve for the planter's optimal effort level conditional on a given piece rate and productivity shock. Then we solve for the firm's choice of the piece rate, taking the reaction of the planter as given. Note that, in order to induce the planter to accept the contract, the contract must satisfy the planter's labour-supply constraint.

Conditional on s, planters choose effort to maximize their utility. The optimal level of effort e is

$$e = \left(\frac{rs}{\kappa_i}\right)^{\gamma_i}$$

giving output

$$y = \left(\frac{r}{\kappa_i}\right)^{\gamma_i} s^{\gamma_i+1}. \tag{4.1}$$

Taking logarithms of both sides of (4.1) yields

$$\log y = \gamma_i \log r - \gamma_i \log \kappa_i + (\gamma_i + 1) \log s,$$

or, in terms of random variables,

$$\log Y_{ij} = \gamma_i \log r_j - \gamma_i \log \kappa_i + (\gamma_i + 1) \log S_{ij} \tag{4.2}$$

where the j subscript denotes plot j and where

$$(\gamma_i + 1) \log S_{ij} \sim \mathcal{N}\big[(\gamma_i + 1)\mu_j, (\gamma_i + 1)^2 \sigma_j^2\big].$$

Note that the parameter γ_i provides a direct measure of the elasticity of planter i's effort with respect to the piece rate. Taking expectations of (4.2) yields

$$\mathcal{E}(\log Y_{ij}) = \gamma_i \log r_j - \gamma_i \log \kappa_i + (\gamma_i + 1)\mu_j. \tag{4.3}$$

Lemma 1:

Differences in the expected logarithm of observed productivity can be decomposed into a part due to differences in ability κ_i and a part due to differences in the response to incentives γ_i.

The proof of this lemma, like the proofs to all our claims, is contained in an appendix to the paper.

Intuitively, higher than average productivity may be due to higher than average ability (strength) or due to higher than average response to the incentives in place.

4.1. Estimation

To convert (4.2) into an equation with a mean-zero error term, we add and subtract $(\gamma_i + 1)\mu_j$. This yields

$$\log Y_{ij} = \gamma_i \log r_j - \gamma_i \log \kappa_i + (\gamma_i + 1)\mu_j + V_{ij} \tag{4.4}$$

where V_{ij} now equals $(\gamma_i + 1)\big(\log S_{ij} - \mu_j\big)$, which is distributed normally with mean zero and variance $(\gamma_i + 1)^2 \sigma_j^2$.

As noted in Paarsch and Shearer (1999), direct estimation of equation (4.4) is problematic because μ_j is unobserved, while μ_j and r_j are correlated. To solve for this endogeneity problem, we model the firm's decision rule in setting the piece rate as a function of μ_j. In the presence of heterogeneous workers, we assume that the expected-utility constraint is binding for a given planter, denoted h. Thus, suppressing the j subscript temporarily, we get

$$\frac{r^{\gamma_h+1}}{\kappa_h^{\gamma_h}(\gamma_h+1)}\mathcal{E}\left(S^{\gamma_h+1}\right)=\bar{u} \tag{4.5}$$

where $\bar{u}$ denotes the reservation utility, which is assumed the same for all planters. Substituting equation (4.5) into equation (4.4) yields

$$\begin{aligned}\log Y_{ij} =&\frac{\gamma_i+1}{\gamma_h+1}\log\bar{u}+\frac{\gamma_i+1}{\gamma_h+1}\log(\gamma_h+1)-\log r_j+\gamma_h\frac{\gamma_i+1}{\gamma_h+1}\log\kappa_h-\\ &\gamma_i\log\kappa_i-(\gamma_h+1)(\gamma_i+1)\frac{\sigma_j^2}{2}+V_{ij}\end{aligned} \tag{4.6}$$

where

$$V_{ij}\sim\mathcal{N}\left[0,(\gamma_i+1)^2\sigma_j^2\right].$$

Equation (4.6) generalizes equation (9) of Paarsch and Shearer (1999), admitting heterogeneous responses to piece rates. In particular, when the γ_is and γ_h are the same, γ, equation (4.6) collapses to equation (9) of Paarsch and Shearer (1999) allowing a test of homogeneous treatment effects. Note that, while heterogeneity in the cost of effort κ only affects the mean in the logarithm of productivity, heterogeneity in response γ affects both the mean and the variance of productivity. This asymmetry provides the key to identification.

4.2. Identification

To consider identification, we reparameterize (4.6) as

$$\log Y_{ij}+\log r_j=\alpha_0+\sum_{i=2}^{89}\alpha_{1i}DW_i-0.5\sum_{i=1}^{89}\sum_{j=1}^{31}\psi_i\tilde{\sigma}_j^2 DW_i\times DP_j+V_{ij} \tag{4.7}$$

where DW_i is one for planter i and zero otherwise, while DP_j is one for plot j and zero otherwise. Note that 89 and 31 denote the number of planters and plots, respectively. Here,

$$\begin{aligned}
\psi_i &= \frac{\gamma_i + 1}{\gamma_h + 1} \\
\alpha_0 &= \psi_1 \left[\log \bar{u} + \log(\gamma_h + 1) + \gamma_h \log \kappa_h\right] - \gamma_1 \log \kappa_1 \\
\alpha_{1i} &= (\psi_i - \psi_1)\left[\log \bar{u} + \log(\gamma_h + 1) + \gamma_h \log \kappa_h\right] + \gamma_1 \log \kappa_1 - \gamma_i \log \kappa_i\,. \\
\tilde{\sigma}_j^2 &= (\gamma_h + 1)\sigma_j^2 \\
V_{ij} &\sim \mathcal{N}(0, \psi_i^2 \tilde{\sigma}_j^2)
\end{aligned}$$

Claim 1:

The model identifies

$$\alpha_0,\ \alpha_{1i},\ \psi_i,\ \tilde{\sigma}_j^2.$$

The model admits identification of a ranking rather than the level of planter-specific effort elasticities. To see this note that γ_i is monotonically related to ψ_i via

$$\gamma_i = (\gamma_h + 1)\psi_i - 1.$$

While identifying the ranking of elasticities is sufficient for our present purposes, we also consider conditions under which actual elasticities are recoverable. Identifying the level of planter-specific elasticities requires that planter h be present in the sample, and that a measure of alternative utility be available. This is summarized in the following:

Claim 2:

Let individual h (for whom the expected-utility constraint is binding) be in the sample. Then, conditional on a measure of the reservation utility $\bar{u}$, the structural model identifies:

$$\gamma_h, \gamma_i, \sigma_j^2.$$

Note that a test of individual h being in the sample is equivalent to testing that ψ_i equals one for some i. Note too that the hypothesis of homogeneous treatment effects is equivalent to testing that ψ_i equals one for all i. Despite the fact that γ_h is the value of γ for the indifferent individual, it is not necessarily the maximum value of γ in the firm since planter-specific heterogeneity extends over two parameters in this model γ and κ. As such, a test of ψ_i equal one has a two-sided alternative.

5. Empirical Results

We estimated the model in three ways. First, we used a two-step method to estimate the relationship between the ψ_i parameters and gender. In the first step, we estimated the ψ_i terms as planter-specific parameters in equation (4.7). We then regressed the estimated planter-specific parameters on planter-specific characteristics, including gender. Under the second method, we specified that ψ_i equal $g(\boldsymbol{x}_i, \boldsymbol{\delta})$, a non-stochastic function of observed characteristics. This allowed us to estimate the relationship between ψ_i and the planter's gender directly in equation (4.7). The third method admitted unobserved heterogeneity in ψ_i via $g(\boldsymbol{x}_i, \boldsymbol{\delta}, \xi_i)$ where ξ_i is a planter-specific component, unobserved by the econometrician and independent of $\boldsymbol{x}_i$.

5.1. Two-Step Estimation

The results from estimating the parameters of equation (4.7), treating the ψ_is as planter-specific parameters, are presented in Table 4. To save space, we report only the average as well as maximum and minimum estimated planter-specific parameters.

Table 4
First-Stage Parameter Estimates
Sample Size = 3960

Planter-Specific Parameters				
Parameter		Estimate	Std. Error	p-Value
α_0		4.972	0.034	0.000
Maximum $\alpha_i = \alpha_{28}$		0.675	0.045	0.000
Minimum $\alpha_i = \alpha_{83}$		-0.496	0.049	0.000
Average $\hat{\alpha}_i$	0.245			
Std Dev $\hat{\alpha}_i$	0.224			

Planter-Specific Elasticity Parameters				
Parameter		Estimate	Std. Error	p-Value
Maximum $\psi_i = \psi_{26}$		0.754	0.154	0.000
Minimum $\psi_i = \psi_{52}$		0.169	0.039	0.000
Average $\hat{\psi}_i$	0.398			
Std Dev $\hat{\psi}_i$	0.107			

Variance Parameters				
Parameter		Estimate	Std. Error	p-Value
Maximum $\sigma_j = \sigma_{29}$		1.088	0.239	0.000
Minimum $\sigma_j = \sigma_{24}$		0.057	0.053	0.274
Average $\hat{\sigma}_j$	0.591			
Std Dev $\hat{\sigma}_j$	0.214			

Logarithm of the Likelihood Function:	19.935

The logarithm of the likelihood function was 19.935. The estimated ψ_is were all less than one, with the maximum being 0.754. This suggests that the indifferent individual responds the most to incentives. A test of the homogeneous-treatment-effect model, that ψ_i equals one for all i, was conducted using the likelihood-ratio test. The restricted logarithm of the likelihood was -209.02; see Paarsch and Shearer (1999) Table 4(b). There are 209 parameters in the unrestricted model and 120 in the restricted, so the likelihood-ratio statistic was 457.92 with 120 degrees of freedom; the p-value for this is effectively zero. Thus, we conclude that planters do differ with respect to their effort elasticities; some planters respond more to incentives than others.

To consider the relative performance of male and female planters, we focussed on the estimated ψ_is which are graphed in Figure 1. The estimated ψ_is for male and female planters are graphed in Figure 2. There exists little evidence in these graphs suggesting a difference between men and women. To investigate further the relative response of male and female planters, we regressed the estimated ψ_is on planter characteristics, including age and gender. Specifically, we estimated the following regression:

$$\hat{\psi}_i = \delta_0 + \delta_1 DM_i + \delta_2 AGE_i + \delta_3 AGESQ_i + \varepsilon_i. \tag{5.1}$$

The results from this regression are presented in Table 5. Along with the OLS standard errors, we present standard errors that are robust to arbitrary forms of heteroscedasticity as well as bootstrapped p-values for tests of the the null hypothesis that the parameter equals zero. The bootstrapped p-values were calculated using the *wild bootstrap* with 999 draws from the Rademacher distribution to account for heteroscedasticity of unknown form; see, for example, MacKinnon (2002). The form of the heteroscedasticity is unknown because the unobserved heterogeneity affects the true value of ψ_i. In particular, the true relationship between ψ_i and personal characteristics is given by

$$\psi_i = \delta_0 + \delta_1 DM_i + \delta_2 AGE_i + \delta_3 AGESQ_i + \xi_i, \tag{5.2}$$

where ξ_i represents unobserved heterogeneity, independent of characteristics. Substituting ψ_i equal $(\hat{\psi}_i - v_i)$ into (5.2) demonstrates that ε_i equals $(\xi_i + v_i)$ is composed of unobserved heterogeneity and first-stage estimation error. Generalized least-squares can correct for the second-stage heteroscedasticity when the variance of ξ is zero. One simply divides (5.1) by the estimated standard errors of $\hat{\psi}_i$ from the first stage; see Card and Krueger (1992). In general, the variance of ξ_i is greater than zero and the form of the heteroscedasticity in the second stage is unknown.

Table 5 Second-Stage Parameter Estimates
Sample Size = 89

Parameter	Estimated Coefficient	Standard Error	Robust Standard Error	Bootstrapped P-Value
δ_0	0.251	0.175	0.137	0.470
δ_1	-0.011	0.027	0.032	0.632
δ_2	0.008	0.011	0.009	0.490
δ_3	$-8.0(-5)$	$1.7(-4)$	$1.5(-4)$	0.672
R^2: 0.035				

The results in Table 5 are interesting on many levels. First, on average, the estimated ψ_is for men were slightly lower that those for women; however, the difference was not statistically significant. Note too that the R^2 for this regression is 0.035; observable characteristics only explained 3.5 percent of the variation in individual response to incentives. Coupled with the results of Table 4 this suggests that, while individuals respond differently to incentives, these responses are not predictable using observable characteristics.

5.2. Observed Heterogeneity

To incorporate covariate heterogeneity directly into the ψ_is, we specified the function

$$\psi_i = g(\boldsymbol{x}_i\boldsymbol{\delta}). \tag{5.3}$$

Substituting (5.3) directly into (4.7) allowed us to estimate $\boldsymbol{\delta}$. To guarantee that each ψ_i is positive, we used the following parameterization:

$$g(\boldsymbol{x}_i\boldsymbol{\delta}) = \exp(\delta_0 + \delta_1 DM_i + \delta_2 AGE_i + \delta_3 AGESQ_i).$$

The estimated δ_is are presented in Table 6.

These results are consistent with those of the two-step estimation procedure. In particular, while women appear to have reacted slightly more to incentives than did

Table 6
Observed Heterogeneity Parameter Estimates
Sample Size = 3960

Planter-Specific Parameters				
Parameter		Estimate	Std. Error	p-Value
α_0		4.969	0.036	0.000
Maximum $\alpha_i = \alpha_{28}$		5.646	0.052	0.000
Minimum $\alpha_i = \alpha_{83}$		4.472	0.061	0.000
Average $\hat{\alpha}_i$	0.245			
Std Dev $\hat{\alpha}_i$	0.224			

Elasticity Heterogeneity Parameters				
Parameter		Estimate	Std. Error	p-Value
δ_0		-1.150	0.288	0.000
$\delta_1(DM)$		-0.036	0.026	0.159
$\delta_2(AGE)$		0.023	0.014	0.095
$\delta_3(AGESQ)$		$-2.7(-4)$	$2.0(-4)$	0.174

Variance Parameters				
Parameter		Estimate	Std. Error	p-Value
Maximum $\sigma_j = \sigma_{29}$		0.947	0.244	0.000
Minimum $\sigma_j = \sigma_{24}$		0.037	0.020	0.031
Average $\hat{\sigma}_j$	0.504			
Std Dev $\hat{\sigma}_j$	0.181			

Logarithm of the Likelihood Function:	-200.148

men, so $\hat{\delta}_1$ is less than zero, the difference is not statistically significant.[6]

5.3. Unobserved Heterogeneity

Finally, we considered adding unobserved heterogeneity into the ψ_i functions. We made ψ_i a function of both $\boldsymbol{x}_i$ and a planter-specific continuous random variable ξ_i

[6] Note that, while the planter-specific elasticity parameters (the δ_is) are not individually significant, the null hypothesis of a constant elasticity is rejected. Estimating the model with homogeneous planters yielded a logarithm of the likelihood function -209.02, while estimating the model with heterogeneous planters yielded a logarithm of the likelihood function -200.21. A likelihood-ratio statistic has a p-value of 0.001.

which has probability density function $h(\xi_i)$. We then substituted this directly into equation (4.7). To guarantee that each ψ_i is positive, we used the functional form

$$g(\boldsymbol{x}_i\boldsymbol{\delta}, \xi_i) = \exp(\delta_0 + \delta_1 DM_i + \delta_2 AGE_i + \delta_3 AGESQ_i)\xi_i$$

where ξ_i was assumed log-normally distributed, having mean one and variance σ_ξ^2. Conditional on a value of ξ_i, the contribution to the likelihood function individual i, planting on terrain j, is given by

$$f(\log y|\xi_i) = \frac{1}{\sqrt{2\pi}}\frac{1}{\psi(\xi_i)\sigma_j}\exp\left\{\frac{1}{2\psi^2(\xi_i)\sigma_j^2}\left[\log y - \mu_Y(\xi_i)\right]^2\right\};$$

$$\psi(\xi_i) = \exp(\delta_0 + \delta_1 DM_i + \delta_2 AGE_i + \delta_3 AGESQ_i)\xi_i;$$

$$\mu_Y(\xi_i) = \alpha_0 + \sum_{i=2}^{89}\alpha_{1i}DW_i - 0.5\sum_{i=1}^{89}\sum_{j=1}^{31}\psi(\boldsymbol{x}_i\boldsymbol{\delta}, \xi_i)\tilde{\sigma}_j^2 DW_i \times DP_j.$$

Integrating over the unobserved ξ_i yields the likelihood of observation i

$$f(\log y) = \int_0^\infty f(\log y|\xi_i)h(\xi)\ d\xi \tag{5.4}$$

where

$$h(\xi) = \frac{1}{\xi\sigma_\xi}\phi\left(\frac{\log\xi + .5\sigma_\xi^2}{\sigma_\xi}\right)$$

and $\phi(\cdot)$ represents the standard-normal distribution function.

We estimated the model by the method of simulated maximum likelihood where we replaced the integral in (5.4) by summation, so

$$f(\log y) = \sum_{r=1}^{R}\frac{1}{R}f(\log y|\xi_r) \tag{5.5}$$

with ξ_r being a simulated log-normal random variable.

The parameter estimates, based on an R of 500, are presented in Table 7. These results are consistent with our previous findings; namely, in this sample, female

Table 7
Unobserved Heterogeneity Parameter Estimates
Sample Size = 3960

Planter-Specific Parameters				
Parameter		Estimate	Std. Error	p-Value
Maximum $\alpha_i = \alpha_{29}$		5.850	0.040	0.000
Minimum $\alpha_i = \alpha_{84}$		4.628	0.044	0.000
Average $\hat{\alpha}_i$	5.446			
Std Dev $\hat{\alpha}_i$	0.229			

Elasticity Heterogeneity Parameters			
Parameter	Estimate	Std. Error	p-Value
δ_0	-3.014	0.292	0.000
δ_1	-0.003	0.035	0.934
δ_2	0.015	0.017	0.388
δ_3	$-1.7(-4)$	$2.5(-4)$	0.506
σ_ξ	0.423	0.018	0.000

Variance Parameters				
Parameter		Estimate	Std. Error	p-Value
Maximum $\sigma_j = \sigma_{29}$		4.655	0.765	0.000
Minimum $\sigma_j = \sigma_{28}$		2.055	0.379	0.000
Average $\hat{\sigma}_j$	2.995			
Std Dev $\hat{\sigma}_j$	0.574			

Logarithm of the Likelihood Function:	78.928

planters reacted more to incentives than did male planters, but the difference is not statistically significant. In addition, our explanatory variables (age and gender) provide little predictive power as to who will react most to incentives. The estimates of the variance parameters increase relative to those in the observable heterogeneity model due to the constant term in the ψ function.

To consider the overall significance of the predictors in the ψ function, we considered the restricted model for which

$$g^r(\boldsymbol{x}_i\boldsymbol{\delta}, \xi_i) = \exp(\delta_0)\xi_i.$$

Table 8
Unobserved Heterogeneity: Restricted Parameter Estimates
Sample Size = 3960

Planter-Specific Parameters				
Parameter		Estimate	Std. Error	p-Value
Maximum $\alpha_i = \alpha_{29}$		5.845	0.038	0.000
Minimum $\alpha_i = \alpha_{84}$		4.649	0.049	0.000
Average $\hat{\alpha}_i$	5.447			
Std Dev $\hat{\alpha}_i$	0.227			
Elasticity Heterogeneity Parameters				
Parameter		Estimate	Std. Error	p-Value
δ_0		−2.719	0.080	0.000
σ_ξ		0.424	0.018	0.000
Variance Parameters				
Parameter		Estimate	Std. Error	p-Value
Maximum $\sigma_j = \sigma_{29}$		4.646	0.804	0.000
Minimum $\sigma_j = \sigma_{28}$		2.037	0.376	0.000
Average $\hat{\sigma}_j$	2.995			
Std Dev $\hat{\sigma}_j$	0.573			
Logarithm of the Likelihood Function:		77.210		

The parameter estimates are given in Table 8. Most importantly, the value of the restricted likelihood is 77.210. The value of the unrestricted likelihood from Table 7 is 78.928. The likelihood-ratio statistic is equal to 3.437 and the test has three degrees of freedom. The p-value of this calculated test statistic is 0.329, suggesting the restrictions that age and gender have no explanatory power for effort elasticities cannot be rejected.

6. Discussion and Conclusion

Workers differ in productive characteristics, both observed and unobserved. Controlling for these differences is important when interpreting the causes of observed differences in economic outcomes as well as potential policies to overcome those differences. We have used an economic model as an identifying device to decompose observed productivity differences between men and women into two parts: worker ability and their reaction to incentives. Our results suggest there is no significant difference between male and female reactions to incentives within our sample. While individuals do react differently to incentives, in our sample, age and gender offer little or no ability to predict these reactions. The average observed difference in productivity between men and women in our sample is explained by differences in ability, strength within the tree-planting context.

We caution, however, that our results are limited to one firm and do not necessarily generalize. For example, we do not suggest that women react to all incentive schemes in the same manner as do men. Differences in labour-force attachment may lead to differences in reaction to career-oriented incentive schemes such as promotion; see, for example Goldin (1986). Some generalization may, however, be possible. In particular, our results suggest that the observed difference in productivity between men and women is solely attributable to differences in physical strength. In environments where physical strength is unimportant, our results suggest that productivity differentials should disappear, consistent with Gneezy *et al.*. A complete generalization of our results would require identification of the population distribution of elasticities. At the least, this would require estimating a structural model that incorporated both productivity decisions and the decision to participate in the firm. The development and identification of such models remains an important area for future research based on firm-level payroll records.

Finally, our results provide an interesting contrast to historical work in the sociology literature. Some sociologists have argued that men and women react differently to incentives because of differences in their family environments. Shimmin (1962) noted that young female workers in England during the 1950s and 1960s often had their earnings expropriated by their families in return for a fixed allowance. She argued that these social conventions, which did not apply to men, dampened female responses to incentive payments; see Millward (1968) for some evidence of these effects. The contrast with our results undoubtedly reflects the changing circumstances under which women participate in the labour market today.

A. Appendix

In this appendix, we present proofs of the lemma and claims listed in the text of the paper.

Proof of Lemma 1:

Let

$$\mathcal{E}(\log Y_{Mj}) = \gamma_M \log r_j - \gamma_M \log \kappa_M + (\gamma_M + 1)\mu_j$$

represent average productivity of male workers and

$$\mathcal{E}(\log Y_{Fj}) = \gamma_F \log r_j - \gamma_F \log \kappa_F + (\gamma_F + 1)\mu_j$$

represent average productivity of female workers, so

$$\mathcal{E}(\log Y_{Mj}) - \mathcal{E}(\log Y_{Fj}) = (\log r_j + \mu_j)(\gamma_M - \gamma_F) + \gamma_F \log \kappa_F - \gamma_M \log \kappa_M.$$

Adding and subtracting $\gamma_M \log \kappa_F$ yields

$$\mathcal{E}(\log Y_{Mj}) - \mathcal{E}(\log Y_{Fj}) = (\log r_j + \mu_j - \log \kappa_F)(\gamma_M - \gamma_F) + \gamma_M(\log \kappa_F - \log \kappa_M).$$

The difference in average productivity between male and female workers can be decomposed into two parts: differences in the response to piece rates $(\gamma_M - \gamma_F)$ and differences in ability or strength $(\log \kappa_F - \log \kappa_M)$.[7]

Proof of Claim 1:

The parameters collected in the vector $\boldsymbol{a}$ are composites of structural parameters that are not separately identified except under special circumstances; see the claim

[7] When γ and κ are random variables the decomposition holds under the condition that $\operatorname{cov}(\gamma, \log \kappa)$ is independent of gender. In particular,

$$\mathcal{E}(\log Y_M) = \log r \mathcal{E}\gamma_M + (\mathcal{E}\gamma_M + 1)\mu + \mathcal{E}(\gamma_M \log \kappa_M).$$

Using the fact that $\mathcal{E}(\gamma_M \log \kappa_M)$ equals $[\operatorname{cov}(\gamma, \log \kappa) + \mathcal{E}(\gamma_M)\mathcal{E}(\log \kappa_M)]$ yields

$$\begin{aligned}\mathcal{E}(\log Y_{Mj}) - \mathcal{E}(\log Y_{Fj}) = &\left[\log r_j + \mu_j - \mathcal{E}(\ln \kappa_F)\right]\left[\mathcal{E}(\gamma_M) - \mathcal{E}(\gamma_F)\right] + \\ &\mathcal{E}(\gamma_M)\left[\mathcal{E}(\log \kappa_F) - \mathcal{E}(\log \kappa_M)\right].\end{aligned}$$

below. The terms ψ_i and σ_j are identified through the restriction that they determine both the block-specific effects and the variance terms. While each individual adds a parameter ψ_i and each plot adds a parameter $\tilde{\sigma}_j$, observing individuals over multiple plots and multiple individuals on the same plot provides sufficient moment conditions to identify these parameters.

Proof of Claim 2:

Without loss of generality, let individual h be denoted by individual i equal 1. Then ψ_1 equals one and the constant term a_0 which equals $[\log \bar{u} + \log(\gamma_h + 1)]$ identifies γ_h, conditional on a measure of $\bar{u}$. This reflects the identification strategy followed by Paarsch and Shearer (1999).

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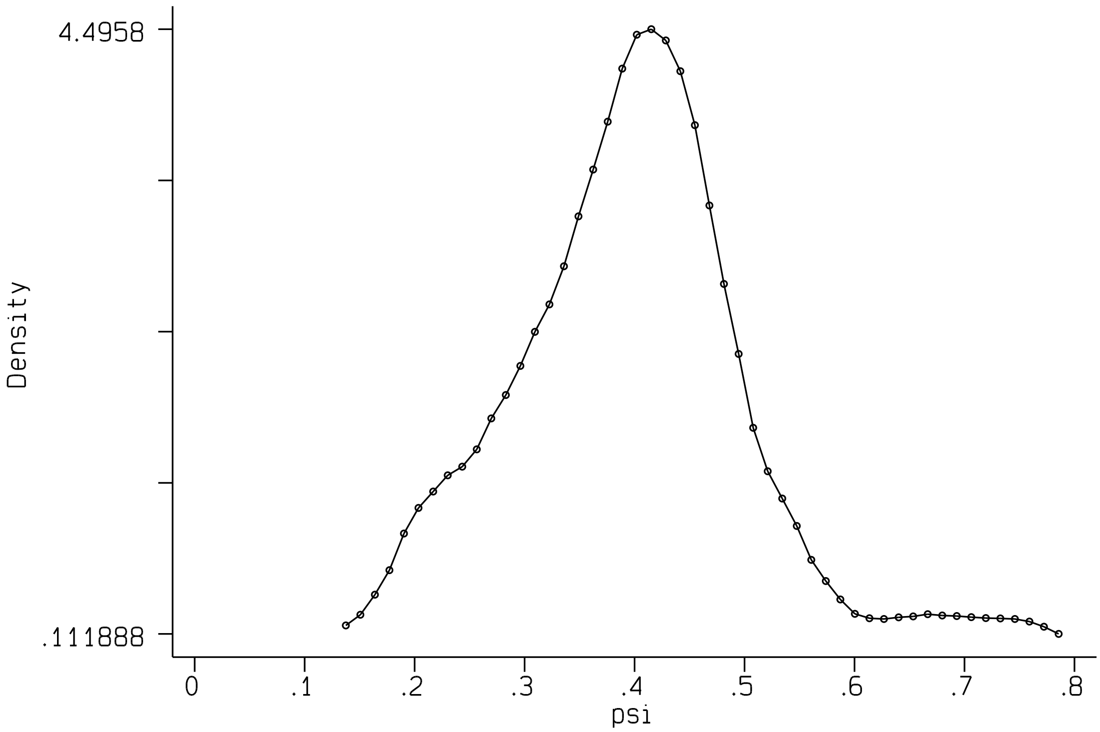
Figure 1: Kernel-Smoothed Density of Psi



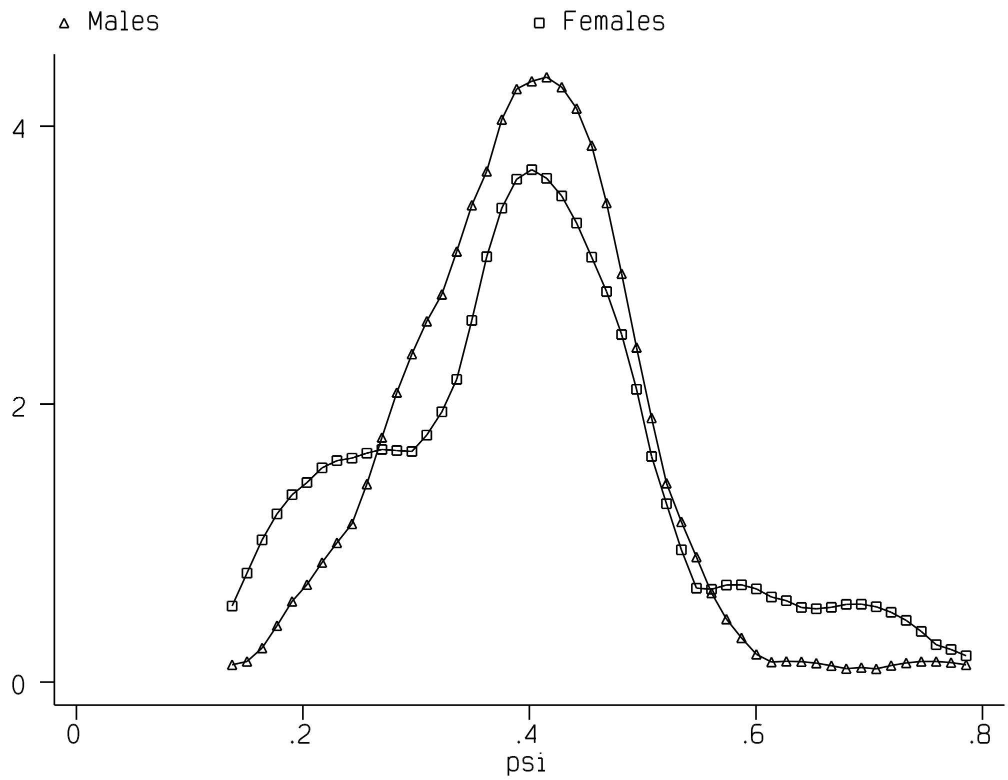


Figure 2: Kernel-Smoothed Density of Psi